Article

Journal of Marketing
2020, Vol. 84(3) 28-45

DOI: 10.1177/0022242920912732
journals.sagepub.com/home/jmx

Full Disclosure: How Smartphones Enhance Consumer Self-Disclosure

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Abstract

Results from three large-scale field studies and two controlled experiments show that consumers tend to be more self-disclosing when generating content on their smartphone versus personal computer. This tendency is found in a wide range of domains including social media posts, online restaurant reviews, open-ended survey responses, and compliance with requests for personal information in web advertisements. The authors show that this increased willingness to self-disclose on one's smartphone arises from the psychological effects of two distinguishing properties of the device: (1) feelings of comfort that many associate with their smartphone and (2) a tendency to narrowly focus attention on the disclosure task at hand due to the relative difficulty of generating content on the smaller device. The enhancing effect of smartphones on self-disclosure yields several important marketing implications, including the creation of content that is perceived as more persuasive by outside readers. The authors explore implications for how these findings can be strategically leveraged by managers, including how they may generalize to other emerging technologies.

Keywords

natural language processing, self-disclosure, technology, user-generated content

Online supplement: https://doi.org/10.1177/0022242920912732

Among the many recent changes in consumer markets, two trends have been particularly transformative. The first is the emergence of online communication as a central medium through which firms and customers interact. This medium has yielded a wealth of textual data including social media posts, online reviews, and chats that can provide firms with real-time insights into customer opinions, needs, and preferences (e.g., Wedel and Kannan 2016). The second trend is the emergence of the smartphone as the dominant platform on which these communications take place. Whereas online activities were once limited to at-home or in-office sessions on personal computers (PCs), with smartphones these activities can now occur at virtually any time and place. As a consequence of these two trends, when firms analyze user-generated content today, it is increasingly likely that it was created by consumers on their smartphone rather than their PC.

In this article, we explore a question that lies at the intersection of these two trends: As consumers continue to generate content on their smartphone, might this shift be altering what consumers share about themselves—and thus what firms can learn about their customers? Across three field studies (and three replication studies) examining thousands of customer-generated posts from various contexts—as well as two preregistered experiments—we provide evidence that content created by consumers on their smartphones tends to be more self-disclosing than that created on PCs. We show, for example, that social media posts and customer reviews written on smartphones tend to be composed in a more personal, intimate linguistic style, and that consumers are more willing to admit certain types of personal information when using their smartphone, such as experiences with products that are private or embarrassing. This effect is robust across different measures (human judgments, automated measures) and different forms of disclosure (e.g., open-ended survey responses, online reviews, compliance rates with calls to action [CTAs] in web ads). Importantly, this effect has significant marketing implications; for example, the more personal and intimate nature of smartphone-generated reviews results in content that is more persuasive to outside readers, in turn heightening purchase intentions.

We also investigate the mechanisms that underlie the observed differences in disclosure, demonstrating that the

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greater tendency to self-disclose on smartphones arises from the combination of two factors unique to the device. The first is that the highly personal nature of smartphones—resulting from both their constant accessibility and frequent use for personal or intimate activities (e.g., texting with family and friends)—fosters distinct feelings of psychological comfort on the device that facilitate users' willingness to self-disclose. Second, the difficulty of creating content on the smaller form of the device (screen and keyboard) leads consumers to narrow their attentional focus to the task at hand, which also facilitates disclosure.

Theoretical Background

What Factors Enhance Willingness to Self-Disclose?

The study of self-disclosure is among the oldest in the social sciences, spanning the fields of psychology (e.g., Cozby 1973; Derlega et al. 1993), human–computer interaction (e.g., Kim and Dindia 2011; Walther 1996), and survey research (e.g., Heberlein and Baumgartner 1978; Weisband and Kiesler 1996). This topic is of growing interest to marketing researchers, who have explored how consumers' willingness to provide personal information over a computer is affected by factors such as the nature of the web interface (e.g., John, Acquisti, and Loewenstein 2011), online privacy policies (Andrade, Kaltcheva, and Wietz 2002), and the degree of reciprocity in an interaction with an agent (Moon 2000). Here, we follow Altman and Taylor (1973) to define "self-disclosure" as the voluntary communication of feelings, thoughts, or other information deemed to be private and that might make the discloser feel vulnerable (see also Cozby 1973; Omarzu 2000). For example, disclosure might involve expressing one's candid feelings about a service experience or admitting to incriminating consumption behaviors.

A primary focus of research in this area has been to identify situational factors that drive people's willingness to self-disclose. For example, while people tend to be inherently protective of their private feelings and thoughts, they are more willing to share personal information when they feel a greater sense of privacy in their environment (e.g., Derlega and Chaikin 1977; Dienlin 2014; John, Acquisti, and Loewenstein 2011) or if they perceive their particular audience as more anonymous (e.g., Kiesler, Siegel, and McGuire 1984; Spears and Lea 1994; Wallace 1999). Likewise, the degree of psychological comfort evoked by a context can drive self-disclosure. Therapists, for example, find that patients tend to be more self-disclosing in physical environments that foster feelings of security and familiarity, or when they feel more at ease with a counterpart in conversation (e.g., Chaikin, Derlega, and Miller 1976; Gifford 1988).

The Role of Modality in Self-Disclosure

Relevant to our work is research examining how different communication modalities affect people's willingness to self-disclose, particularly in computer-mediated versus face-to-face environments (e.g., Bowling 2005; Joinson 2001; Kim and Dindia 2011; Walther 1996; Weisband and Kiesler 1996). A consistent finding in this literature is that people are often willing to disclose more about themselves when communicating over a computer (e.g., email, instant messaging) than in person (e.g., Bowling 2005; Ruppel et al. 2017; Walther 1996). While these effects have been discussed both in terms of depth of disclosure—the sensitivity of what people reveal—and breadth, or the amount revealed, a recent meta-analysis found that communicating through a computer (vs. face-to-face) has a larger effect on depth of disclosure (Ruppel et al. 2017). That is, while people may not necessarily disclose more when communicating through a computer compared to face-to-face, what they do disclose tends to be more intimate.

Although a few explanations have been proposed for why people might disclose more through computers than in person (e.g., Kim and Dindia 2011), accounts generally point to the comparative anonymity of interacting through computer screens (e.g., Walther 1996). Specifically, when people interact in person they receive a wealth of social cues that make them more concerned about how they come across to others (Short, Williams, and Christie 1976). This concern about others' reactions then works to reduce willingness to disclose personal or intimate information in face-to-face interaction (e.g., Carver and Scheier 1981). When one expresses oneself through a computer, however, these social cues are less salient because of the physical distance or isolation of one's audience, which can increase willingness to disclose (e.g., Kim and Dindia 2011; Sassenberg, Boos, and Rabung 2005; Weisband and Kiesler 1996).

While there is consistent evidence that consumers often disclose information that is more intimate or sensitive when communicating over computer-mediated interfaces relative to face-to-face, it is less clear whether depth of disclosure is influenced by the computing interface itself—specifically, smartphones versus PCs. For example, communication on both types of device involves interaction through a screen, suggesting that the salience of social cues—and in turn, users' willingness to disclose—might be similar across devices. Indeed, some limited support for this invariance has been provided by Antoun, Couper, and Conrad (2017), Mavletova and Couper (2013), and Toninelli and Revilla (2016), who found that when sensitive questions were first posed on a mobile device and then later on a PC (and vice versa), respondents showed high test–retest reliability, suggesting that device effects, if they exist, may be small. However, there have been no prior attempts to examine whether the use of smartphones (vs. PCs) affects degrees of self-disclosure in more complex real-world settings, such as when consumers post on social media, write reviews, or respond to open-ended questions on surveys.

How Smartphones Enhance Self-Disclosure Relative to PCs

In this work, we hypothesize that while smartphones and PCs share some commonalities, they differ along two dimensions

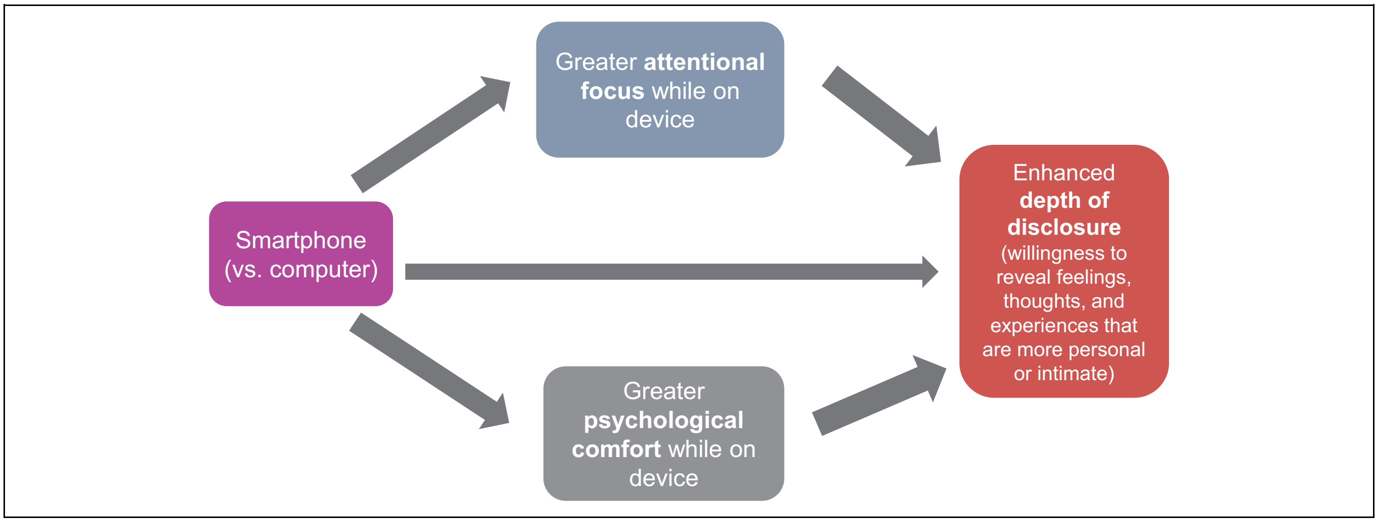

Figure 1. Theoretical process model showing how use of one's smartphone (vs. PC) can lead to greater depth of disclosure.
Notes: The model hypothesizes two parallel causal paths of mediation: one stemming from greater focus on the disclosure at hand, and the other through feelings of enhanced psychological comfort on the device.

that, taken together, influence consumers' willingness to self-disclose: (1) the extent to which consumers experience psychological comfort while on the device and (2) the degree of attentional narrowing arising from the form factor of the device (e.g., size). These two elements, depicted in Figure 1, form the foundation of our main hypothesis:

> **H_1:** Consumers will tend to exhibit enhanced depth of disclosure—sharing personal feelings, thoughts, and other information deemed to be more intimate and private—when creating content on their smartphone versus their PC.

Next, we discuss the process by which we hypothesize that comfort and attentional narrowing lead to greater self-disclosure.

The comforting role of smartphones. The first factor that we argue enhances depth of disclosure on one's smartphone versus PC is the increased psychological comfort that consumers tend to derive from their phone (e.g., Clayton, Leshner, and Almond 2015; Vahedi and Saiphoo 2018). For example, Melumad and Pham (2020) found that after an induction of stress, participants assigned to engage in a task on their smartphone reported a greater increase in psychological comfort (and thus, greater relief from stress) than those assigned to engage in the same task on their laptop, or even an otherwise similar smartphone belonging to someone else.

The enhanced feeling of comfort associated with one's smartphone (vs. other devices) is thought to arise from a unique combination of positive, personal associations with the device (Melumad and Pham 2020). For example, whereas PCs tend to be used more for work purposes, smartphones are often relied on for texting with friends and family, watching entertaining videos, or catching up on social media updates (e.g., Panova and Carbonell 2018; Skierkowski and Wood 2012). Moreover, given their portability, smartphones are almost always within arm's reach—in one's pocket or purse during the day, by one's bedside at night—such that consumers learn that they can rely on their smartphone to engage in these personal activities whenever and wherever they want (e.g., Cheever et al. 2014). As a result, the device becomes a general source of comfort and security for owners (Melumad and Pham 2020).

Critically, this difference in comfort bears important implications for depth of disclosure across devices. Prior work has shown that situational factors—such as mere differences in how a website is designed—can foster enhanced feelings of privacy and security and, thus, greater willingness to self-disclose in online surveys (John, Acquisti, and Loewenstein 2011). These results are consistent with research showing that people are more likely to self-disclose in environments that evoke positive affect (Forgas 2011), such as feelings of comfort and security (e.g., Chaikin, Derlega, and Miller 1976; Gifford 1988; Miwa and Hanyu 2006). We therefore propose the following:

> **H_2:** Consumers are more willing to share sensitive information on their smartphone (vs. PC) in part because they tend to experience greater psychological comfort while on the device.

The smaller form of smartphones. Prior work shows that differences in form influence the process of content generation across smartphones versus PCs. For example, because it is more difficult to write on its smaller keyboard and screen, users tend to generate shorter content on their smartphone (vs. PC) when completing open-ended surveys (e.g., Buskirk and Andrus 2014; Mavletova and Couper 2013; Wells, Bailey, and Link 2014) and writing online reviews (Melumad, Inman, and Pham 2019; Ransbotham, Lurie, and Liu 2019). Given these form-factor constraints, the amount of information that people disclose—or the breadth of self-disclosure—should similarly be lower when sharing from a smartphone versus PC.

Although the smaller form of smartphones (vs. PCs) may limit the amount of information that consumers share, we argue that it has the countervailing effect of enhancing depth of disclosure, or the intimacy of information disclosed. One line of evidence consistent with this prediction comes from Melumad, Inman, and Pham (2019), who found that when consumers write reviews on their smartphone versus PC, they tend to use a greater proportion of emotional words (e.g., "love," "amazing"). Although expressions of emotionality do not necessarily imply more self-disclosure per se, enhanced emotionality is widely considered one of several linguistic markers of greater depth of disclosure (e.g., Houghton and Joinson 2012).

The rationale for our hypothesis is as follows. A large body of research shows that when tasks are more difficult, people tend to respond by focusing more intently on the most essential aspects of the task in lieu of peripheral information (e.g., Castiello and Umiltà 1990; Chen, Liao, and Yeh 2011; Murphy, Groeger, and Greene 2016). As such, the relative difficulty of engaging in activities on a smartphone due to its smaller keyboard and screen may similarly narrow users' attention to the task they are engaging in on the device. Consistent with this, research shows that smartphone users often experience "inattentional blindness" when using their device, narrowing their focus to the activity onscreen while blocking out external surroundings (e.g., Hyman et al. 2010; Lin and Huang 2017). As an illustration of this narrowing effect, a large-scale field study found that 46% of pedestrians who were on their smartphone failed to notice a unicycling clown passing within one meter of them (Chen and Pai 2018).

Building on this, we propose that when engaging in disclosure of personal information on one's smartphone (vs. PC), the relative difficulty of completing the task on its smaller keyboard and screen will similarly focus users on the most essential elements of the task—sharing one's personal thoughts and feelings—and less on peripheral thoughts and cues that might otherwise inhibit disclosure. This prediction is consistent with recent work demonstrating that people asked to complete an online survey while under cognitive load (i.e., remembering names)—possibly paralleling the difficulty of generating content on a smartphone (vs. PC)—were more willing to respond to sensitive survey questions (Veltri and Ivchenko 2017). Formally, we hypothesize,

> **H_3:** The smaller form of smartphones (vs. PCs) narrows consumers' attention down to the communication at hand, which, in turn, enhances depth of disclosure when generating content on the device.

Overview of Studies

We report the results of five empirical studies that support the proposed effect of device use on depth of disclosure in user-generated content, as well as explore the mechanisms underlying the observed differences (Figure 1). We begin by offering large-scale field evidence for the basic effect in analyses of tweets about a variety of topics (Study 1) and analyses of online restaurant reviews (Study 2). In two preregistered experiments we then test for the causal effect of device use on self-disclosure, as well as the proposed underlying mechanisms (Studies 3 and 4). We conclude by demonstrating the real-world generality of the effect by examining consumers' compliance with sensitive CTAs in web ads across devices (Study 5).

Study 1: Depth of Disclosure Across Devices on Twitter

The purpose of the first field study was to test for the proposed differences in depth of disclosure on a major social media platform, Twitter. To control for potential differences across devices in both the timing of posts and topical content, we analyzed a data set of 369,161 original tweets[1] that each included one of 203 "trending hashtags" within a single 12-hour period in December 2015.[2] The hashtags covered a wide range of topical domains—including pop culture, sports, and a terrorist attack that occurred in San Bernardino, California—which allowed us to test for the generalizability of any observed differences between smartphones and PCs.

Data Preprocessing

Prior to the main analysis, the data underwent four waves of preprocessing. First, a dichotomous indicator of whether a tweet was written on a smartphone or PC was created by identifying each tweet's originating platform (e.g., a tweet written on a smartphone would be evidenced by "Twitter for iPhone," and on PC by "Twitter Web Client"); tweets originating from ambiguous or unknown sources (e.g., third-party apps) were removed, leaving 296,473 original tweets. Because we were interested in analyzing tweets generated by typical users rather than commercial networks or professional bloggers, in the second stage of preprocessing we removed 1,305 tweets with known commercial usernames (e.g., CNN) or that were posted from accounts with exceptionally large followings, which we defined a priori to be the top 1% of the distribution of followers (more than 32,978 followers).[3] This yielded a final data set of 293,039 tweets (59.6% originating from smartphones). Next, to allow for a within-user analysis of differences in depth of disclosure, the third stage of preprocessing involved identifying the 2,121 users from the total set of qualified users who tweeted from *both* a PC and smartphone.

[1] These data come from a master corpus of 9 million tweets that were scraped in early December 2015. This same master corpus was the basis for a separate subset of data used in Melumad, Inman, and Pham (2019) to test a different theory (using different measures).

[2] A preliminary analysis confirmed that there were no significant differences in the average time of posting between devices across the hashtag categories.

[3] Given their small representation in the data (1%), the statistical results are robust to the exclusion of commercial accounts.

In the final wave of preprocessing, the 203 "trending hashtags" in our data were topically categorized by human judges. To achieve this, we recruited a sample of 150 Amazon Mechanical Turk (MTurk) participants and first asked them to familiarize themselves with ten randomly assigned hashtags (of the possible 203) by clicking on a hyperlink that led them to a set of tweets that had recently included the hashtag. After participants felt familiar with the content associated with an assigned hashtag, they were instructed to indicate whether it belonged to one or more of seven possible categories: news (e.g., #CaliforniaShooting), sports (e.g., #ArmyNavy), entertainment/pop-culture (e.g., #GoldenGlobes), amusement (e.g., #ImAWreckCause), moral causes (#GenocideVictimsDay), technology (e.g., #GoogleDemoDay), and economy/finance (#futureofwork). This process yielded roughly 15 judgments for each of the 203 hashtags, and each hashtag was categorized on the basis of the grouping (e.g., "news," "sports") to which it was most frequently assigned.[4]

Method and Results

We undertook two approaches to analyzing whether tweets created on smartphones showed greater depth of self-disclosure than those created on PCs: an automated analysis of linguistic markers (e.g., use of first-person pronouns; see, e.g. Davis and Brock 1975) as well as human assessments of the content. Each of these approaches will be described in turn.

Automated measures of depth of disclosure. Multiple researchers have sought to identify linguistic markers indicative of greater self-disclosure in text (e.g., Bak, Lin, and Oh 2014; Brockmeyer et al. 2015; Davis and Brock 1975; Pennebaker and Graybeal 2001; Wang, Burke, and Kraut 2016). To illustrate these markers, in Web Appendix 1 we provide examples of texts from each of our studies that were assessed by human judges as being high or low in self-disclosure. Consistent with prior work on the linguistic markers of self-disclosure, the examples show how texts judged to be self-disclosing tend to be accompanied by more extensive use of (1) first-person pronouns (e.g., "I," "me"), (2) references to family and friends, and (3) words that convey emotionality—particularly negative emotions (Houghton and Joinson 2012; Okdie 2011). The presence of these common linguistic markers forms the foundation of algorithms designed to automatically detect depth of disclosure in online texts (Bak, Kim, and Oh 2012; Balani and De Choudhury 2015; Ravichander and Black 2018; Wang, Burke, and Kraut 2016).

Drawing on this extant literature, we subjected the tweets to analysis by Linguistic Inquiry and Word Count (LIWC; Pennebaker, Boyd, and Jordan 2015), which contains dictionaries for each of the aforementioned linguistic markers (first-person pronouns, references to family and/or friends, and negative emotionality).[5] We also examined LIWC measures for "authentic" and "analytical" writing styles. According to Pennebaker, Boyd, and Jordan (2015), writers using a more authentic style create texts that are more personal and vulnerable, such that higher authenticity scores point to greater depth of disclosure. Moreover, texts written in a less analytical style, as indicated by more narrative language and references to personal experiences, would also be suggestive of greater depth of disclosure.

Finally, to ensure that the LIWC analysis provided valid measures of the degree of self-disclosure in tweets, we undertook a cross-validation analysis that regressed human judgments of the depth of disclosure for a sample of the tweets on each of the six LIWC measures of disclosure (see Web Appendix 2 for a description of the method and results). The findings confirmed, for example, that tweets rated as more self-disclosing by human judges tended to include a greater proportion of first-person pronouns and references to family and friends, and were written in a more authentic—but less analytic—writing style as measured by LIWC.

Results: differences in depth of disclosure based on automated measures. In Table 1 we report the results of two statistical approaches to analyzing how the linguistic content of tweets created on smartphones differs from that created on PCs. One approach involved a set of six univariate analyses that modeled each of the LIWC dimensions of interest (e.g., use of first-person pronouns, analytical and authentic writing styles) as a function of the originating device. The second was a multivariate logistic regression that predicted the likelihood of a tweet being written on a smartphone versus PC as a function of the six LIWC dimensions simultaneously. The analyses controlled for the word count of the texts—which tends to be greater for content written on PCs versus smartphones (Melumad, Inman, and Pham 2019)—as well as for the hashtag categories.[6] Finally, the table reports separate results for the overall corpus of tweets as well as a within-user analysis of the subset of users who tweeted from both devices, which allowed us to better control for possible issues of self-selection across devices.

The results provide strong initial support for H_1 among the full data set of tweets as well as the subset of users who tweeted from both devices. For the full data set, across hashtag categories tweets written on smartphones tended to contain greater proportions of first-person pronouns ($M_{smartphone} = 3.29$ vs. $M_{PC} = 2.23$; $F(1, 293{,}038) = 2{,}742.45$, $p < .001$), references to family ($M_{smartphone} = .76$ vs. $M_{PC} = .50$; $F(1, 293{,}038) =$

[4] For example, if a hashtag was judged by 62% of MTurk judges as focusing on news and 38% as focusing on finance, it was categorized as a "news" hashtag for the purpose of analysis.

[5] Exploratory analyses of other LIWC categories indicated that tweets written on smartphones (vs. PCs) also tended to use relatively more informal language (i.e., netspeak, nonfluencies, swear words). While a more informal writing style might also point to greater self-disclosure on smartphones, we focus on the four linguistic markers that have been validated in prior work (e.g., Ravichander and Black 2018).

[6] Models estimated controlling for neither the hashtag category nor word count yielded similar results.

Table 1. Study 1: Univariate Least-Square Mean Differences Between Smartphone- and PC-Generated Tweets Along LIWC Dimensions and Coefficients of Multivariate Logistic Regression Modeling the Likelihood That Tweets Were Written on Smartphones (vs. PCs) as a Function of These Dimensions.

	Univariate Tests of Least-Square Means							
	Entire Corpus (N = 293,039)				Users Tweeting on Both Devices (N = 41,452)			
Trait	PC	Smartphone	F	Pr > F	PC	Smartphone	F	Pr > F
Analytical style	72.98	69.08	1,059.54	<.001	70.97	69.54	126.17	<.001
Authentic style	25.49	28.94	681.54	<.001	25.68	29.00	287.06	<.001
First person	2.23	3.29	2,742.45	<.001	2.52	3.20	244.55	<.001
Family	.50	.76	714.18	<.001	.55	.64	112.70	<.001
Friends	.25	.32	142.79	<.001	.28	.34	37.07	<.001
Negative emotion	1.52	1.62	40.73	<.001	1.34	1.55	98.18	<.001
Word count	14.70	13.12	3,816.09	<.001	13.50	12.56	201.08	<.001
	Multivariate Logistic Models (Criterion: Smartphone-Generated Tweet)							
	Entire Corpus (N = 293,039)				Users Tweeting on Both Devices (N = 41,452)			
	Word Frequencies		Linguistic Style		Word Frequencies		Linguistic Style	
Trait	Estimate	Pr > χ^2	Estimate	Pr > χ^2	Estimate	Pr > χ^2	Estimate	Pr > χ^2
Analytical style			−.004	<.001			−.001	.008
Authentic style			.002	<.001			.003	<.001
First person	.033	<.001			.03	<.001		
Family	.023	<.001			.01	<.001		
Friends	.022	<.001			.02	<.001		
Negative emotion	.005	<.001			.01	<.001		
Word count	−.041	<.001	−.0036	<.001	−.02	<.001	−.02	<.001
	Model Fit		Model Fit		Model Fit		Model Fit	
	LR χ^2	% Concordant	LR χ^2	% Concordant	LR χ^2	% Concordant	LR χ^2	% Concordant
	8,202.16	59.4	5,278.53	64.4	985.13	58.1	866.58	57.6

Notes: Analytical and authentic writing styles are measured as scores out of 100, whereas types of words are measured as percentages. The effects of writing styles were modeled separately because the scores are composites of some of the word-use measures.

681.54, $p < .001$) and friends ($M_{smartphone} = .32$ vs. $M_{PC} = .25$; $F(1, 293{,}038) = 142.79$, $p < .001$), and negative emotional words ($M_{smartphone} = 1.62$ vs. $M_{PC} = 1.52$; $F(1, 293{,}038) = 40.73$, $p < .001$). These results are further supported by differences in writing style across devices: tweets written on smartphones tended to display a less analytical but more authentic writing style (analytical: $M_{smartphone} = 69.08$ vs. $M_{PC} = 72.98$; $F(1, 293{,}038) = 1{,}059.54$, $p < .001$; authentic: $M_{smartphone} = 28.94$ vs. $M_{PC} = 25.49$; $F(1, 293{,}038) = 681.54$, $p < .001$). As shown in Table 1, the within-user analyses of tweets written by the same users on their smartphone and PC yielded a similar pattern of results.

Finally, we examined whether the size of these effects varied by the particular hashtag category (e.g., sports, politics). The results (reported in Web Appendix 3) suggest that while many of the aggregate results hold across the hashtag categories, there was some variance in the size and, in some cases, direction of the effects. For example, while the use of first-person pronouns and references to family and friends were consistently greater on smartphones in domains that are intuitively more amenable to self-disclosure—such as news (e.g., #CaliforniaShooting), moral causes (e.g., #GenocideVictimsDay), pop culture (e.g., #CouplesTherapy), and sports (e.g., #FIFA)—these same markers were less evident in the more impersonal domains of finance (e.g., #DiscussTheDeals) and technology (#bufferchat). These latter two categories also showed less authentic and more analytical writing styles, a reversal that is perhaps unsurprising given the conversational norms that generally surround discussions of finance and technology (e.g., a tone that is more objective than subjective).

Human judgments of depth of disclosure. To provide further evidence for differences in disclosure, we subjected the full set of tweets from two of the hashtag categories—2,261 tweets about the San Bernardino terrorist attack (53% smartphone), and 1,009 tweets about pop culture (56% smartphone)—to assessment by human judges. These two categories were selected so that we could test for the effect across topics that differed substantively in context and valence. We recruited an independent sample of 1,925 MTurk participants to assess up to 10 randomly selected tweets, yielding an average of 7.08 judgments per tweet. Participants were blind to both the hypothesis of this study and the originating device of the tweet.

To measure depth of disclosure in the tweets, participants rated their agreement with a set of items used in prior work (e.g., Barak and Gluck-Ofri 2007; Jourard and Lasakow 1958; Wang, Burke, and Kraut 2016) on a seven-point scale (1 = "Not at all," and 7 = "Very much so"):

1. *Self-focus*: "To what extent does the writer focus on him/herself in this tweet (e.g., how he/she felt, what he/she did)?"
2. *Internal states*: "To what extent does the writer reveal his or her personal feelings, thoughts, or opinions?"
3. *Personal information*: "To what extent does the writer disclose personal information about him/herself?"
4. *Vulnerable*: "To what extent does the writer disclose information that might make him/her feel emotionally vulnerable?"
5. *Controversial*: "To what extent is the writer expressing potentially controversial statements/views?"
6. *Offensive*: "To what extent is the writer expressing views that may be offensive to others?"
7. *Impulsive*: "To what extent does it seem like the writer was impulsive when writing his/her tweet?"

An exploratory factor analysis revealed that these items loaded onto two dimensions of disclosure: "intimate information" (self-focus, internal states, personal information, vulnerable; $\alpha = .78$) and "lack of censorship" (controversial, offensive, impulsive; $\alpha = .85$). Web Appendix 1 shows examples of tweets that scored high versus low on intimacy of information disclosed.

Results: differences in depth of disclosure based on human judgments. Paralleling the analyses of the automated measures, we undertook two sets of analyses of the human assessments of the tweets. The first set included two univariate analyses that separately modeled our measures of perceived depth of intimate disclosure and lack of censorship as a function of the originating device, and the second set involved a multivariate logistic analysis that predicted the likelihood that a tweet had been written on a smartphone or a PC as a function of the perceived depth of intimate disclosure and lack of censorship (simultaneously). As with the automated analysis, each model controlled for the word-count differences between devices.

The results provide convergent validity for the central hypothesis that consumers express greater depth of disclosure when writing on their smartphone versus PC. First, tweets written on smartphones (vs. PCs) were assessed by judges as conveying more intimate information—an effect that held for the tweets about both the San Bernardino attack ($M_{smartphone} = 3.04$ vs. $M_{PC} = 2.84$; $F(1, 7{,}854) = 34.47$, $p < .001$) and the pop-culture topics ($M_{smartphone} = 5.01$ vs. $M_{PC} = 2.76$; $F(1, 5{,}180) = 2{,}210.08$, $p < .001$). In contrast, while tweets written on smartphones were judged as more uncensored on average (see Web Appendix 4), the effect was primarily driven by the tweets about pop-culture topics ($M_{smartphone} = 5.73$ vs. $M_{PC} = 3.71$; $F(1, 5{,}169) = 1{,}297.90$, $p < .001$), as there was no perceived difference in degree of censorship among tweets about the San Bernardino attack ($M_{smartphone} = 4.15$ vs. $M_{PC} = 4.16$; $F < 1$). Thus, tweets posted from smartphones were consistently viewed as more intimately self-disclosing than those posted from PCs, and were less consistently seen as more unfiltered or uncensored. (The results of the multivariate logistic regression, which models the likelihood of the tweets being written on a smartphone versus PC as a function of the two human-judged dimensions of disclosure, mirror these results; see Web Appendix 4.)

Discussion and Replication Studies

The results of the first field study provide initial evidence that user-generated content written on smartphones tends to convey greater depth of disclosure than content written on PCs (H_1). This effect was robust across both automated measures (e.g., percentage of first-person pronouns, references to family) and human judgments of disclosure. These results were also robust across a variety of contexts that ranged from serious breaking-news events (a terrorist attack) to frivolous online amusements (e.g., "#TheWorstSecretSantaGifts").

Although we find that the pattern of results consistently held across the hashtag categories in our data set, to further test for the robustness of this effect we conducted the same analyses reported above for three additional Twitter data sets. Two were obtained from public sources: (1) a corpus of 67,408 tweets about the 2018 FIFA World Cup posted on Kaggle (Rituparna 2018), and (2) a corpus of 201,258 tweets posted about the 2016 U.S. presidential election on election day (King 2016). We also analyzed (3) an original corpus of 18,346 tweets on hashtags covering news, sports, and amusement/entertainment on a single day in January 2017. The results of these analyses, reported in Web Appendix 5, closely replicate those reported above: Whether users were tweeting about a sporting event, election, or entertaining topic, tweets written on smartphones (vs. PCs) consistently contained greater proportions of first-person pronouns, references to family and friends, and emotional words—particularly those conveying negative affect. They also tended to have a more authentic and less analytical style.

Study 2: Does Self-Disclosure Matter? An Analysis of Online Reviews

Study 1 offered initial evidence that at least one type of user-generated content—tweets about a variety of topics—tends to contain greater depth of disclosure when written on smartphones versus PCs. One important question, however, is whether the observed differences in depth of disclosure might yield meaningful downstream marketing implications. Prior work would suggest, for example, that content written in a more self-disclosing manner would lead readers to feel a greater sense of similarity to the writer, which may result in content that is more persuasive to outside readers (Jiang et al. 2010; see also Faraji-Rad et al. 2015). In Study 2 we therefore tested for the robustness of the effect in a domain in which self-disclosure might have material impacts on consumer behavior: online restaurant reviews on TripAdvisor.

Method

The data set contained a corpus of 10,185 TripAdvisor restaurant reviews written on smartphones or PCs between April 2014 and July 2017. The reviews were a random sample drawn from a larger corpus utilized in previous work (Melumad, Inman, and Pham 2019) and were comparably balanced between smartphones (N = 5,097) and PCs (N = 5,088). The data included the name of the restaurant, date of the visit, and text of the review. Mirroring the approach to analysis in Study 1, we undertook two analyses to measure the depth of disclosure in the reviews. The first was to subject the texts to analysis by LIWC, which as in Study 1 yielded measures of a battery of linguistic markers of self-disclosure (e.g., first-person pronouns).

The second approach subjected the same reviews to assessment by MTurk judges who rated the reviews along two dimensions. The first was the perceived depth of disclosure, measured along two items adapted from Study 1 that were relevant in the context of restaurant reviews: "To what extent did the writer focus on him/herself in this review (e.g., how he/she felt, what he/she did)?" and "To what extent did the writer reveal his or her personal feelings, thoughts, or opinions?" (α = .63). Importantly, two additional measures were now included to capture a potential downstream consequence: "How persuasive would you find this review to be if you were considering going to this restaurant?" and "How interested would you be in visiting this restaurant?" As in Study 1, all items were measured on a seven-point scale (1 = "Not at all," and 7 = "Very much so"), with participants blind to the hypothesis and originating device of the review.

Results

Differences in depth of disclosure based on automated measures. As in Study 1, we undertook both univariate and multivariate logistic regression analyses of the degree to which content written on smartphones differed from that written on PCs along a battery of LIWC measures that are suggestive of self-disclosure: use of first-person pronouns, references to family/friends, negative emotionality, and authentic and analytical styles. Again, the analysis controls for differences in word count, which was significantly higher in PC-generated reviews ($M_{smartphone} = 69.87$ words vs. $M_{PC} = 96.28$ words; $F(1, 10{,}182) = 347.76$, $p < .001$).

Note that because reviews are, by definition, personal—typically first-person—accounts of one's consumption experience, logically the vast majority of reviews should appear self-disclosing (at least to some extent). Still, even in this comparatively self-disclosing context, the results conceptually replicate those of Study 1. Reviews written on smartphones tended to include greater proportions of first-person pronouns ($M_{smartphone} = 2.35$ vs. $M_{PC} = 2.19$; $F(1, 10{,}182) = 9.55$, $p = .002$), references to family ($M_{smartphone} = .38$ vs. $M_{PC} = .32$; $F(1, 10{,}182) = 9.55$, $p = .002$) and friends ($M_{smartphone} = .52$ vs. $M_{PC} = .43$; $F(1, 10{,}182) = 36.34$, $p < .001$), and negative emotional words ($M_{smartphone} = .75$ vs. $M_{PC} = .67$; $F(1, 10{,}182) = 7.09$, $p = .008$). Finally, as in Study 1 smartphone-generated reviews had a less analytic writing style ($M_{smartphone} = 64.43$ vs. $M_{PC} = 65.95$; $F(1, 10{,}182) = 9.40$, $p = .002$), though here we did not find a difference in authentic writing style ($M_{smartphone} = 34.63$ vs. $M_{PC} = 35.07$; $F < 1$). (Binary logistic regression analyses, presented in Web Appendix 6, yield similar results.)

Differences in depth of disclosure and persuasiveness based on human judgments. Next, we undertook the same analyses as in Study 1 to test for differences in human assessments of the content. Consistent with Study 1, the results show that reviews written on smartphones (vs. PCs) were rated as containing greater depth of disclosure ($M_{smartphone} = 4.67$ vs. $M_{PC} = 4.52$; $F(1, 9{,}551$[7]$) = 18.10$, $p < .001$). The results also provide evidence for a key downstream implication of this effect: reviews written on smartphones were rated by judges as being more persuasive than those written on PCs ($M_{smartphone} = 4.97$ vs. $M_{PC} = 4.74$; $F(1, 9{,}540) = 49.40$, $p < .001$). Finally, readers were more interested in visiting restaurants reviewed by other customers on their smartphones than restaurants reviewed on PCs (least square $M_{smartphone} = 4.68$ vs. $M_{PC} = 4.61$; $F(1, 9{,}840) = 3.90$, $p = .048$)—an effect that was strengthened after we controlled for valence of the review (as captured by the percentage of negative emotional words; $M_{smartphone} = 4.69$ vs. $M_{PC} = 4.60$; $F(1, 9{,}539) = 5.74$, $p = .016$).

Next, we conducted a serial mediation analysis (SAS Proc Calis) to test whether reviews with greater depth of disclosure in smartphone-generated content led to greater persuasiveness and, thus, greater interest in the restaurant under review. The results provided an excellent fit to the data (Bentler comparative fit index = .998; root mean square residual = .008) and, critically, supported the hypothesized model. Reviews written on smartphones (vs. PCs) contained greater depth of disclosure ($b_{device \rightarrow disclosure} = .05$; $t = 4.79$, $p < .001$); reviews containing greater depth of disclosure were more persuasive ($b_{disclosure \rightarrow persuasive} = .28$; $t = 30.06$, $p < .001$); and more persuasive reviews heightened readers' interest in visiting the restaurant ($b_{persuasive \rightarrow interest} = .62$; $t = 96.67$, $p < .001$). Finally, the model supported an overall positive indirect effect of device on interest in visiting the restaurant (total indirect effect: $b_{device \rightarrow disclosure \rightarrow persuasive \rightarrow interest} = .03$; $t = 4.71$, $p < .001$).

Discussion

Across two field studies we provide consistent evidence that customers tend to convey greater depth of disclosure when

[7] Differences in degrees of freedom across these analyses arose because of missing responses to some scale items for certain reviews.

generating content on their smartphone than on their PC—as evidenced by tweets about a variety of topics (Study 1) and by restaurant reviews (Study 2). It is worth noting that the size of the effects was somewhat smaller among the restaurant reviews (e.g., Cohen's d for human-judged depth of disclosure = .09) compared with the tweets (Cohen's d = .14)—a result that is not surprising given that, by construction, customer-generated reviews are first-person accounts of personal consumption experiences, making it harder to observe differences in degree of disclosure across devices. Nevertheless, even in this context, reviews written on smartphones still exhibited greater depth of disclosure than those written on PCs.

Study 2 also indicates that the greater depth of disclosure in smartphone-generated content carries important downstream consequences. Outside readers found reviews written on smartphones (vs. PCs) to be more persuasive, which, in turn, heightened their interest in visiting the restaurant under review. These results are broadly consistent with those of Grewal and Stephen (2019), who found that reviews containing a mobile indicator (e.g., a "written on mobile" label) are more persuasive to outside readers than those containing a PC indicator. They argued that this occurred because readers infer that mobile-generated reviews are more credible given the relative difficulty of writing on the device. It is important to emphasize, however, that the outside readers in our study were given no information about the device on which the content was written, such that reviews written on smartphones (vs. PCs) were rated as more persuasive based solely on their content.

Finally, it is worth noting that one possible explanation for why reviews and/or tweets written on smartphones (vs. PCs) appeared more self-disclosing is that they were composed at the same time as an event or experience, when personal feelings may have been more salient. Two results, however, argue against such a timing explanation: (1) restaurant reviews written on smartphones included relatively *more*—not fewer—references to the past ($M = 6.90$) than those written on PCs ($M = 6.33$; $F(1, 10{,}182) = 42.39$, $p < .001$) and (2) the tweets in Study 1 were posted nearly simultaneously from smartphones and PCs. Nevertheless, because the association between smartphone use and self-disclosure remains correlational, and the underlying mechanism remains uncertain, in the next two studies we attempt to increase our knowledge by investigating the effect in a more controlled setting.

Study 3: Testing for Underlying Mechanisms

The purpose of Study 3 was twofold. The first aim was to test whether the differences in depth of disclosure observed in the first two field studies replicate in a more controlled setting wherein participants are randomly assigned to generate content on their smartphone or PC. The second aim was to test whether the greater depth of disclosure in smartphone-generated content is driven by the proposed mechanisms for the effect: first, a greater sense of psychological comfort (H_2), and second, greater attentional narrowing on one's smartphone versus PC (H_3).

Method

Study 3 involved two data-collection phases. In the first phase, participants were randomly assigned to use their smartphone or PC to write about an upsetting personal experience; in the second phase, participants' descriptions of their personal experience were evaluated by an independent sample of judges for depth of disclosure. In this section, we describe each of these phases in turn.

Phase 1: eliciting disclosures and measuring proposed mediators. We preregistered this study on AsPredicted.org, which included the preregistration of our predicted hypotheses as well as exclusion criteria.[8] Our final data set included responses from 715 participants from a Qualtrics panel (60% female) who were randomly assigned to complete a two-part survey on either their smartphone or their personal computer (for the complete survey instrument, see Web Appendix 7). In the first part of the survey—which served to administer the disclosure task—participants were asked to use their assigned device to describe an upsetting personal experience (in four to five sentences). The specific instructions were as follows:

> Think of a topic or event in your life that made you upset (e.g., an article you read that made you angry; an argument you had with a friend that upset you). In the space below please describe what made you upset, including your thoughts and feelings about the topic or event.

After participants completed the disclosure task, they were asked to use the same device to respond to a set of scales that measured the proposed drivers of depth of disclosure:

1. *Psychological comfort.* Participants responded to five items adapted from Melumad and Pham (2020) that measured the extent to which they associated feelings of psychological comfort with the use of their assigned device (1 = "Not true at all," and 7 = "Very true"): (1) "Using my smartphone (PC) provides a source of comfort," (2) "Having my smartphone (PC) with me makes me feel secure," (3) "When I am using my smartphone (PC) I feel I am in my safe space," (4) "Just holding my smartphone (PC), no matter what I do with it, makes me feel comforted," and (5) "Touching or holding my smartphone (PC) makes me feel calmer." Responses to these items were averaged into an index of "psychological comfort" ($\alpha = .88$).

[8] The data set was originally composed of 1,040 descriptions that were subjected to two preregistered exclusion criteria: descriptions were excluded if they (1) contained content unrelated to the task (e.g., nonsense words, text copied from unrelated sources) and/or (2) were either too brief (<15 words) or too poorly written to be assessed by human judges. Of all the open ended-responses, 229 (22%) were excluded on this basis. An additional 77 responses were deleted for failing two embedded attention checks. Preregistration is available at http://aspredicted.org/blind.php?x=d7vx69.

2. *Attentional narrowing on disclosure.* Participants indicated the extent to which they agreed with each of three statements about how they felt while writing about their personal experience: (1) "I drowned out my environment when writing," (2) "I got lost in what I was writing," and (3) "I felt a sense of privacy when writing" (1 = "Not true at all," and 5 = "Very true"). Responses to these items were averaged to create an index of "attentional narrowing" ($\alpha = .66$).

Next, although our theory does not make direct predictions about whether consumers accurately perceive the depth of disclosure of their own writing, to explore this we asked participants to rate their beliefs about the sensitivity of the information that they shared in their descriptions. This was measured in terms of their agreement with four items (on a five-point scale): "I would hesitate to share this experience with someone I just met," "I felt I was revealing something very personal about myself when describing this experience," "The experience is a very private matter," and "There were sensitive parts of that experience that I intentionally chose not to write about." Responses to these four items were combined to form a "self-judged disclosure" index ($\alpha = .77$).[9]

Finally, to control for possible factors that might additionally influence depth of disclosure across devices, we asked participants to indicate (1) whether they had completed the study in a private or public setting, and 2) the extent to which they were generally concerned about privacy issues on their assigned device. Responses were based on their agreement with two items on a five-point scale: "There are some things that I avoid doing on my smartphone (PC) (e.g., finance-related activities)" and "I worry a lot about the privacy of the data on my smartphone (PC)" ("general privacy concern" index; $\alpha = .83$).

Phase 2: human judgments of depth of disclosure. To measure the key dependent variable—depth of disclosure in the descriptions as perceived by outside judges—we recruited an independent sample of 649 judges from MTurk to assess up to ten randomly assigned texts written by respondents in the main study (judges were blind to both originating device and hypothesis). After reading each text, participants were asked to rate it along the same four items that were used to create the "intimate disclosure" index in Studies 1 and 2 ($\alpha = .76$). We obtained three assessments for each description, yielding a total of 2,129 judgments.

Analyses and Results

Differences in depth of disclosure. As in the first two studies, to test for differences in depth of disclosure across devices we undertook analyses using both automated measures and human judgments of the texts. For the automated analysis, the 715 descriptions were subject to analysis by LIWC (Pennebaker, Boyd, and Jordan 2015), from which we extracted the same set of linguistic markers of self-disclosure analyzed in the previous studies. Similar to the previous results, descriptions written by participants on their smartphones made greater use of personal pronouns ($M_{smartphone} = 14.36$ vs. $M_{PC} = 13.26$; $F(1, 713) = 4.97$, $p = .026$), contained more references to family ($M_{smartphone} = 1.71$ vs. $M_{PC} = 1.16$; $F(1, 713) = 7.02$, $p = .008$), and expressed greater negative emotionality, though this effect did not reach the a priori level of significance ($M_{smartphone} = 5.57$ vs. $M_{PC} = 5.00$; $F(1, 713) = 3.29$, $p = .07$; Wald $\chi^2 = 3.38$, $p = .06$). In contrast, here we did not see a significant difference in references to friends ($M_{smartphone} = .65$ vs. $M_{PC} = .62$; $F < 1$) or in writing styles (authentic: $M_{smartphone} = 37.72$ vs. $M_{PC} = 39.70$; $F < 1$; analytical: $M_{smartphone} = 53.33$ vs. $M_{PC} = 53.89$; $F < 1$).

External judges' assessments of the descriptions provided more direct evidence for differences in depth of disclosure. As we predicted, participants assigned to use their smartphone to write about an upsetting personal experience created content that was rated by outside judges as more disclosing ($M = 4.85$) compared with content created by participants assigned to use their PC ($M = 4.55$; $F(1, 1{,}911) = 22.09$, $p < .001$). Importantly, this effect was sustained after controlling for factors that might covary with depth of disclosure, such as the length of the descriptions as well as the age and gender of the writers (depth of disclosure: least square $M_{smartphone} = 4.84$ vs. $M_{PC} = 4.56$; $F(1, 1{,}908) = 17.08$, $p < .001$). The results also hold after we control for the setting in which the writers completed the study—though it is worth noting that, across conditions, 93% of participants completed the study in a personal (vs. public) place.

Evidence for proposed mechanisms. To investigate whether the effect of device use on depth of self-disclosure could be explained by the proposed mediation model (Figure 1), we estimated a structural path model that included the hypothesized drivers of the effect. The model hypothesized that the direct effect of smartphone (vs. PC) use on human-judged depth of self-disclosure is described by two causal paths: one in which smartphone use evokes greater feelings of psychological comfort, thereby enhancing depth of disclosure (device $\rightarrow$ psychological comfort $\rightarrow$ disclosure), and another in which smartphone use leads to more narrowed attention on the communication at hand, which also enhances depth of disclosure (device $\rightarrow$ attentional narrowing $\rightarrow$ disclosure).

We obtained maximum-likelihood estimates of the path coefficients using SAS's Proc Calis, and they supported the hypothesized causal structure. Specifically, the analysis supported the parallel positive path from smartphone (vs. PC) to psychological comfort ($b_{device \rightarrow comfort} = .05$; $t = 1.98$, $p = .024$), and a positive path from comfort to depth of disclosure ($b_{comfort \rightarrow disclosure} = .35$; $t = 1.79$, $p = .037$). Likewise, the analysis confirmed a significant positive effect of smartphone

[9] The original survey also included the item "The experience I wrote about reveals something about who I am as a person." An exploratory factor analysis, however, indicated that this item loaded onto a second dimension that was unrelated to the other items, and we therefore excluded it from the index.

(vs. PC) use on degree of attentional narrowing on the disclosure task ($b_{\text{device} \rightarrow \text{attentional narrowing}} = .07$; $t = 3.05$, $p = .001$), and a significant positive path from attentional narrowing to depth of disclosure ($b_{\text{attentional narrowing} \rightarrow \text{disclosure}} = 1.27$; $t = 3.95$, $p < .001$). The results also showed a significant total indirect effect of smartphone (vs. PC) use on depth of disclosure through the parallel paths of attentional narrowing and psychological comfort (total indirect effect: $b = .10$; $t = 4.61$, $p < .001$).

Additional analyses: self-judged disclosure and privacy concerns. We undertook two additional analyses for which we did not make a priori predictions. We first examined whether the observed differences in depth of disclosure arose for participants' own perceptions of their descriptions. Notably, the results revealed that participants assigned to write on their smartphone indeed rated their description as more disclosing ($M = 2.88$) than did those assigned to write on their PC ($M = 2.69$; $F(1, 713) = 5.22$, $p = .023$). Thus, both outside readers and the writers themselves appeared to perceive the greater depth of disclosure of smartphone-generated content.

We next examined whether participants' general privacy concerns might influence depth of disclosure across devices. First, as might be expected, participants in the smartphone condition were more likely to agree with the statement, "There are some things that I avoid doing on my [device]; e.g. finance-related activities" compared with those in the PC condition ($M_{\text{smartphone}} = 3.47$ vs. $M_{\text{PC}} = 3.11$; $F(1, 713) = 11.21$, $p < .001$). Interestingly, however, this greater general privacy concern on smartphones did not seem to influence depth of disclosure on the device. Privacy concerns were not statistically correlated with outside judges' assessments of the depth of disclosure (Pearson $r = -.01$; $p = .729$; $N = 1{,}913$) but were *positively* correlated with participants' own perceptions of the depth of disclosure in their accounts (Pearson $r = .15$; $p < .001$; $N = 715$). As a result, inclusion of privacy concerns as a covariate did not alter the effect of device on external judgments of disclosure (least square $M_{\text{smartphone}} = 4.86$ vs. $M_{\text{PC}} = 4.54$; $F(1, 1{,}910) = 22.84$, $p < .001$), but it did temper the effect of device on self-perceptions of disclosure (least square $M_{\text{smartphone}} = 2.98$ vs. $M_{\text{PC}} = 2.72$; $F(1, 712) = 2.85$, $p = .051$).

Discussion

Study 3 provides a conceptual replication of the findings of the two field studies, showing that participants randomly assigned to write about an upsetting personal experience on their smartphone generated content that revealed greater depth of disclosure than did those assigned to use their PC. This effect was observed not only in terms of the automated measures and external human judgments analyzed in the prior studies, but in terms of the writers' own perceptions of depth of disclosure in their descriptions. The results also show that the effects observed in the prior studies generalize to another domain of user-generated content of potential interest to firms: a context wherein consumers are asked to reveal private information in an open-ended survey. Finally, and most importantly, the results of Study 3 provide initial evidence in support of the proposed mechanisms underlying the effect. As we hypothesized, the greater depth of disclosure in smartphone-generated content was driven by a greater sense of psychological comfort on the device (H_2) as well as more narrowed attention on the disclosure task at hand (H_3).

Study 4: Disclosure of Sensitive Consumer Information

In a second experiment, we explored whether the findings of the first three studies generalize to a context that is often of importance to marketers: customer compliance with requests for private or sensitive information. In Study 4 we therefore asked participants to describe a private and potentially embarrassing product experience, with a focus on whether those using their smartphone (vs. PC) would be more willing to comply with the request rather than opt out of doing so.

Method

An independent sample of 1,389 participants was recruited from a Qualtrics panel (71% female) and randomly assigned to complete the study either on their smartphone or their PC. We preregistered the study on AsPredicted.org,[10] which included the preregistration of our predicted hypotheses as well as the same exclusion criteria as in Study 3. The general procedure was similar to that used in Study 3, involving two data-collection phases. The first phase asked participants to disclose a product that they had purchased which they considered to be private and potentially embarrassing (by responding in an open-ended text box) and then to describe their experience with that product (in a second open-ended text box on the subsequent screen). The specific instructions were as follows:

> This survey is part of a market research study aimed at helping companies better understand consumers' experiences with different types of products. Think of a product that you use, or have used in the past, which you consider to be private and possibly embarrassing—that is, something that you might not want others to know about. For example, perhaps you have purchased products to prevent hair loss—or perhaps you sometimes buy certain foods to binge on when you're feeling sad. In the spaces below, please first indicate what this product is (e.g., "weight loss supplement"). Then, please tell us about your experience with this product, such as what led you to buy it, and how you feel about using it.

The key dependent variables of interest were (1) whether participants were willing to disclose such a product or whether they opted out of doing so (e.g., by writing "N/A") and, if they complied with the request for information, (2) the depth of disclosure expressed in their description of the product (which we measured in phase 2). Finally, participants were asked to

[10] Preregistration is available at http://aspredicted.org/blind.php?x=kr7j3g.

use their assigned device to respond to the same items as those used in Study 3 to measure the proposed mechanisms—their psychological comfort ($\alpha = .86$) and attentional narrowing on the task at hand ($\alpha = .68$)—as well as a series of questions measuring possible covariates and demographic information (see Web Appendix 8).

For phase 2 of the study, we first identified the subset of 975 participants who did disclose a private product (and met the preregistered inclusion criteria),[11] and we then recruited a separate sample of 374 MTurk judges to rate the descriptions on two dimensions. The first dimension was the sensitivity of the product described, which was measured based on judges' agreement with the following items (1 = "Not at all," = 7 = "Very much so"): "This product was . . . " (1) "very private," (2) "potentially embarrassing," (3) "not one that would be discussed with a stranger," (4) reveals something personal about the user, and (5) "very intimate." Responses to these items were combined into an index of "product sensitivity" ($\alpha = .92$). The second dimension was the depth of disclosure in the descriptions, which was measured using the same items as in Study 3 ($\alpha = .77$). Thus, while our main analysis compared across devices the rates of compliance (or participants' willingness to disclose the personal product vs. opting out), this second phase enabled us to compare the depth of disclosure conveyed in participants' product descriptions, conditional on their having disclosed one.

Results and Discussion

Differences in response compliance. Across conditions, 134 (11%) of all participants refused to comply with the request to describe a private or sensitive product, as indicated by responses such as "none" (73%) or "I do not buy these types of products" (27%). More importantly, as we predicted, rates of compliance differed between conditions. Participants were significantly more likely to disclose a private or embarrassing product purchase when responding on their smartphone (93%) versus their PC (86%; likelihood-ratio $\chi^2 = 13.35$, $p = .003$). This effect still held after controlling for three measured factors that may have incidentally contributed to differences in compliance across devices: the gender of participants, their age, and whether the study was completed in a public place (least square $M_{smartphone} = .94$ vs. $M_{PC} = .85$; likelihood-ratio $\chi^2 = 23.14$, $p < .001$).

Differences in depth of disclosure (conditional on compliance). We next tested whether there were differences in the depth of disclosure in the product descriptions among the subset of participants who were willing to disclose such a product. Again, the results show that smartphone-generated content was assessed by outside judges as more self-disclosing than that generated on PCs. Specifically, products disclosed by participants on their smartphone were rated by outside judges as more sensitive in nature than those disclosed on PCs ($M_{smartphone} = 4.54$ vs. $M_{PC} = 4.35$; $F(1, 4{,}803) = 4.54$, $p < .001$), and the accompanying descriptions of their products were also rated as conveying greater depth of self-disclosure ($M_{smartphone} = 4.83$ vs. $M_{PC} = 4.70$; $F(1, 4{,}741) = 13.41$, $p < .001$).[12] In contrast, unlike in Study 3, where all participants complied with the writing task, members of this self-selected group of participants were unaware that they were being more self-disclosing when writing about their habits, as here we found no significant difference in self-perceptions of depth of self-disclosure between devices ($M_{smartphone} = 3.29$ vs. $M_{PC} = 3.31$; $F < 1$).

Evidence for mechanisms. To test for the proposed drivers of differences in depth of disclosure, we undertook two structural equation analyses: one for the decision to comply with the disclosure task (vs. opting out) and another for the depth of disclosure in the product descriptions provided by those who did comply. In this particular study, given that one of the proposed mechanisms—degree of attentional narrowing on the disclosure task—was meaningful only for participants who actually agreed to disclose, our analysis of participants' willingness to comply examined only the mediating effect of the degree of psychological comfort associated with the device. Our analysis for differences in depth of disclosure among participants who did comply, in contrast, examined the full set of mediators (as in the prior studies).

For the analysis of differences in rates of compliance, path model estimates derived using SAS's Proc Calis supported the theorized mediating effect of psychological comfort. As we predicted, smartphones (vs. PCs) were associated with greater psychological comfort ($b_{device \rightarrow comfort} = .12$; $t = 4.25$, $p < .001$), and greater psychological comfort was associated with a higher probability of compliance ($b_{comfort \rightarrow compliance} = .08$; $t = 3.48$, $p < .001$). Critically, we also observed a significant indirect effect of device on compliance through comfort ($b = .01$; $t = 2.68$, $p = .007$). Thus, the greater willingness to comply with a request for private information was in part driven by the enhanced feeling of psychological comfort that participants associated with their smartphone versus PC (H_2).

Next, to test for the proposed drivers of depth of disclosure as in Study 3, we collected MTurk assessments of the product descriptions provided by the subset of participants who disclosed the private product. As in Study 3, we estimated the model in which depth of disclosure was driven by two parallel paths: one in which smartphones yield greater psychological comfort (device → comfort → self-disclosure) and another in which smartphones induce greater attentional narrowing on the disclosure task (device → attentional narrowing → self-disclosure). For this study, we measured depth of disclosure as a latent construct with two manifest measures: sensitivity of the

[11] Of the 1,197 respondents who disclosed a private product, 222 provided narratives that failed the preregistered criteria (e.g., too short for textual analysis), leaving 975 descriptions for analysis.

[12] The effect of device on depth of disclosure is strengthened when we controlled for the length of the description, which tended to be longer on PCs ($M_{smartphone} = 4.85$ vs. $M_{PC} = 4.69$; $F(1, 4{,}740) = 21.52$, $p < .001$).

product described and sensitivity of the information conveyed in the product description ($r = .54$; $\alpha = .70$).[13]

The model provided an excellent fit to the data (Bentler comparative fit index = .998; root mean square residual = .000) and offered support for the hypothesized causal structure. Consistent with H_2, we find support for positive path coefficients leading from smartphone (vs. PC) to psychological comfort ($b_{device \rightarrow comfort} = .12$; $t = 8.37$, $p < .001$), and from psychological comfort to depth of disclosure ($b_{comfort \rightarrow disclosure} = .39$; $t = 5.43$, $p < .001$). Likewise, consistent with H_3, we find support for positive path coefficients from smartphone (vs. PC) to attentional narrowing ($b_{device \rightarrow attentional\ narrowing} = .03$; $t = 1.91$, $p = .028$), and from attentional narrowing to depth of disclosure ($b_{attentional\ narrowing \rightarrow disclosure} = .10$; $t = 6.13$, $p < .001$).

Study 5: Compliance with CTAs in Web Ads

To test for the real-world generalizability of the results of Study 4, in the final field study we again examined whether consumers were more willing to provide sensitive information on their smartphone versus PC. To do this, we collaborated with the advertising technology company Taboola (https://www.taboola.com), which provided data on the daily performance of 19,962 CTA web ad campaigns that were run on both smartphones and PCs between November 2018 and August 2019. The data included a total of 631,013 observations representing each of the dates on which the 19,962 campaigns were run.

Call-to-action ads are of interest because they request personal information from consumers to further interact with the firm or brand. The ad campaigns spanned 22 different categories (e.g., finance, music, family) and varied widely in the sensitivity of the product/service advertised (e.g., online games, fitness products, financial services) as well as the depth of personal information that was being requested (e.g., email addresses, estimated credit scores). Web Appendix 9 provides examples of the CTAs for several ad categories. For each ad campaign run on a given date, the data included information about the platform on which the ad was targeted (smartphone, PC), the ad category to which it belonged (e.g., health, dating, lifestyle), the number of consumers who were presented with the ad (i.e., impressions[14]), and the number of consumers who complied with the information request in the ad (i.e., conversions). To test whether consumers were more responsive to CTAs eliciting personal information on their smartphone or PC (H_1), we calculated the conversion rate (i.e., the number of conversions divided by the number of impressions) for each ad category on each platform, which served as our main dependent variable.

[13] We obtain similar path-model results when the two measures of disclosure are modeled separately.

[14] We counted an impression in this data set only if an ad was successfully served to viewers (e.g., an ad blocked by an ad blocker would not register as an impression).

Results and Discussion

The campaigns included in the data reached extremely large audiences, achieving 75.8 billion impressions over the ten-month period of study. As is commonly the case with web ads, however, the rate at which consumers clicked on the ads and provided all the requested information—recorded as a conversion—was quite low (e.g., Manchanda et al. 2006), with 84.68% of all ad-dates reporting no conversions on either PC or smartphone. To account for this highly skewed distribution of responses, we subjected the conversion rates across devices to a series of negative binomial regressions that modeled conversion rates as a function of (1) the device on which the ad was administered and (2) fixed effects that controlled for variance in conversion rates across ad categories, as well as interactions between the device and ad category.

The results of these analyses, summarized in Web Appendix 10, robustly support H_1. Consistent with the results of Study 4, consumers were more likely to comply with requests for personal information in ads when using their smartphone versus PC. Specifically, CTA ads on smartphones had an average conversion rate of .28%, whereas those on PCs had an average conversion rate of .02% ($t = 12.48$, $p < .001$; see Web Appendix 10). This effect was larger when analyzing just the subset of ad dates for which there were nonzero conversion rates. Here, the average conversion rate on smartphones was .54% relative to .03% on PCs ($t = 25.89$, $p < .001$). While the difference in the conversion rates is small in absolute terms, the .26% increase in conversions on smartphones (vs. PCs) translates to millions of customer responses when applied to the billions of impressions achieved across the campaigns.

One natural concern with this analysis is that the higher conversion rates on smartphones may have accrued to factors other than users' willingness to self-disclose per se, such as differences in the contexts in which the devices are used or how the ads are displayed/formatted. If consumers are indeed more willing to self-disclose on their phone (vs. PC), differences in conversion rates should be larger among ad categories where the information elicited is more personal or sensitive in nature, such as ads for dating sites, financial services, and health products; in contrast, conversion rates should be more comparable for categories that are less sensitive, such as music, food, and news. We therefore examined how differences in conversion rates varied by ad category.

To test the association between the sensitivity of the ads and compliance across devices, Taboola provided ad content for a random sample of 1,061 ads from each of the 23 categories that, importantly, included descriptive titles for each ad (e.g., "Calculate Your Maximum Social Security Benefit Instantly" from the "finance" category). We then recruited 686 MTurk participants to assess (on a seven-point scale) up to ten of the ad titles along three correlated items measuring the personal nature and sensitivity of the ad: "This ad is about a very sensitive/private topic," "If I responded to this ad I would expect to be asked a number of personal questions (e.g., my address, finances)," and "If I provided information requested in this ad I feel I would be disclosing something intimate or private about myself." We averaged across these items to create a "personal/sensitive nature" index for each ad title ($\alpha = .70$).

We then estimated the following negative binomial regression, which modeled the observed conversion rates for each of the individual ad campaigns as a function of device, judged sensitivity of each ad category (from which ads were sampled), and the interaction between sensitivity and device:

$$CR_{ijk} = b_o + b_1 D_k + b_2 S_{ij} + b_3 D_k \times S_{ij}$$

where CR_{ijk} is the observed conversion rate for ad campaign i from ad category j on device k, D_k is a dichotomous indicator for device k (smartphone = 1, desktop = −1), S_{ij} is the judged sensitivity of ad campaign i from category j, and $b_0, \ldots, b_3$ are empirical parameters. The key parameter of interest is the coefficient of the interaction between device and sensitivity ($D_k \times S_{ij}$).

The results, presented in Web Appendix 11, confirmed that consumers were more likely to comply with calls to action in ad categories that were more personal and/or sensitive on a smartphone versus a computer. Specifically, we find a positive effect of smartphone (vs. PC) (b = 1.98; t = 4.27; $p < .001$), as well as a negative main effect of perceived ad sensitivity (b = −.34; t = −2.53; $p = .011$) on conversion rates. More importantly, we find a positive interaction between device and ad sensitivity on conversion rates (b = .40; t = 2.78; $p = .005$), suggesting that, as hypothesized, the tendency for conversion rates to be higher on smartphones (vs. PCs) is enhanced for ads that are more personal or sensitive in nature.

As an illustration of this interaction effect, the three categories judged to be the most sensitive on average—dating (M = 4.64), financial services (M = 3.88), and health (M = 3.56)—were associated with the largest differences in average conversion rates between smartphones and PCs (dating: $M_{\text{smartphone − PC diff.}} = .67\%$, $p < .001$; financial: $M_{\text{smartphone − PC diff.}} = .51\%$, $p < .001$; health: $M_{\text{smartphone − PC diff.}} = .40\%$, $p < .001$). In contrast, categories judged to be among the least sensitive in nature—music (M = 2.13), fashion (M = 2.87), and pets (M = 2.93)—showed very limited compliance overall, and no statistically significant difference between smartphones and PCs (music: $M_{\text{smartphone − PC diff.}} = -.0004\%$, $p = .164$; fashion: $M_{\text{smartphone − PC diff.}} = -.002\%$, $p = .096$; pets: $M_{\text{smartphone − PC diff.}} = -.008\%$, $p = .514$; see Web Appendix 12).

General Discussion

In recent years, smartphones have increasingly come to supplant personal computers as the major medium through which consumers provide and share information. In this work we offer evidence that this change has served to alter not only how consumers communicate but also what they share: across five experimental and field studies, we find that consumers tend to be more self-disclosing on their smartphones than their PCs. We find this effect robustly across (1) multiple domains of user-generated content (e.g., six field data sets, open-ended survey responses), (2) different forms of self-disclosure (e.g., self-generated posts, admissions of embarrassing information), and (3) different measures of disclosure (automated measures, external human judgments, the writers' own perceptions of depth of disclosure, and compliance with sensitive CTAs in ads). We also find evidence for the two proposed parallel drivers of this effect, showing that enhanced disclosure on smartphones (vs. PCs) is driven by greater feelings of psychological comfort that consumers associate with their phone and the relative difficulty of generating content on the device, which narrows attention on the disclosure task at hand (and away from peripheral cues or thoughts).

One question that remains is whether consumers are generally aware that they disclose differentially across their devices; for example, when consumers use their phone to tweet, are they aware that they may be revealing more about themselves? While in Study 3 participants reported being more disclosing after completing the disclosure task on their phone versus PC, it is not clear whether they were aware of a general effect of this device. To examine this issue more directly, we recruited an independent sample of 544 MTurk participants and asked them to indicate their beliefs about their willingness to disclose across devices.[15] We also administered similar scales to those used in Studies 3 and 4 to measure the degree to which participants believed that they experience greater psychological comfort and attentional narrowing on their smartphone versus PC. All responses were this time rendered on comparative scales, which were anchored at 1 ("Much more true of my laptop") and 5 ("Much more true of my smartphone"), with 3 ("Equally true of my laptop and smartphone") serving as the midpoint.

The results suggest that consumers seem to be generally aware of the differences in self-disclosure observed in our studies. Respondents indicated that they tend to be more self-disclosing when creating content on their smartphone compared with their PC ($M_{\text{disclosure}} = 3.13$; $t(545) = 3.42$, $p < .001$). Furthermore, participants reported that they generally associate stronger feelings of psychological comfort ($M_{\text{comfort}} = 3.69$; $t(545) = 21.36$, $p < .001$) and tend to feel a greater attentional narrowing in activities ($M_{\text{attentional narrowing}} = 3.52$; $t(545) = 16.99$, $p < .001$) when using their smartphone versus PC. Thus, consumers seem to be at least somewhat aware of the distinct psychological experiences they undergo on their smartphone versus PC, as well as the differences in the types of information they tend to disclose across devices.

Strategic Implications for Managers

The finding that consumers are more willing to self-disclose on their smartphone (vs. PC)—and the identified mechanisms that give rise to it—hold several actionable implications for

[15] To measure participants' self-reported disclosure behavior, we constructed a new index based on four items: "When I use this device to post content on social media, chat with friends, etc. I tend to be . . . " (1) "less censored," (2) "less inhibited," (3) "more honest in what I write," and (4) "more disclosing of what I really think or feel" ($\alpha = .87$).

marketers. Perhaps the most direct is that if a firm wants to obtain sensitive or personal information from consumers, it should target them on their smartphone rather than their PC. We found evidence for this in Study 4, for example, where participants who were asked to admit to purchasing a private or embarrassing product were 6% *less* likely to do so when asked on their PC than when asked on their smartphone. While small in absolute terms, this difference would be quite meaningful for any firm relying on consumer self-reports to gauge consumption rates. Further evidence is provided from the large-scale field data in Study 5, where consumers were more compliant when ads requesting information were targeted on their smartphone (vs. PC)—a difference that was especially large for requests that were more sensitive in nature. Again, while the absolute size of this effect may seem small ($M_{smartphone - PC\ diff.}$ = .19%; $M_{smartphone}$ = .28% vs. M_{PC} = .09%), when applied to the billions of impressions produced by the ad campaigns, this difference in compliance rates potentially translates to millions of additional customer leads for firms.

The finding that social media posts and open-ended survey responses produced on smartphones were more self-disclosing also suggests that smartphone-generated content may offer more diagnostic or accurate insights into consumer preferences. Consistent with this, in Study 3 participants self-reported that they had disclosed information that was more private and personal on their smartphone than did participants on their PC. Building on this result, future work might explore whether the observed effects generalize to domains of disclosure with a measurable benchmark of "truth" or accuracy of information. For example, might consumer preferences disclosed on smartphones (vs. PCs) be more predictive of market outcomes?

Finally, we found that the greater depth of disclosure in smartphone-generated content has the major downstream consequence of being more persuasive to outside readers. Study 2 demonstrated that restaurant reviews written on smartphones were perceived as 5% more persuasive on average than those written on PCs and, when positive, were associated with a 2% increase in readers' interest in visiting the restaurant. The effect of device use was even larger on the high extremes of the perceived persuasiveness and interest scales. Reviews written on smartphones were 33% more likely to receive a "7" on a seven-point scale of persuasiveness (raw difference +4.5%) and 28% more likely to receive a "7" on a seven-point scale of interest in visiting the restaurant (raw difference +3.9%). Thus, firms could identify which reviews will be more persuasive to outside customers by simply identifying their originating device.

Leveraging the Psychological Drivers to Enhance Self-disclosure

In our research we showed that content produced on smartphones (vs. PCs) tends to be more self-disclosing because of two drivers: (1) the tendency for smartphones to be associated with heightened psychological comfort and (2) the narrowing of attention that often arises while completing a task on the device. We conceptualize these drivers as two independent factors with a relative influence that likely varies across consumers as well as contexts. For example, consumers vary in the degree to which they derive psychological comfort from their phone as a function of whether they use the device more for work versus hedonic purposes (Melumad and Pham 2020). Nevertheless, according to our theory, consumers who derive little psychological comfort from their phone might still be more self-disclosing when generating content on the device because of the narrowing of attention that tends to arise when writing on its smaller keyboard and screen. Similarly, one might conjecture that attentional narrowing would not arise when performing a simple task on one's phone, such as clicking a multiple-choice button when responding to survey questions; in such cases, however, consumers might still show enhanced depth of disclosure due to the feelings of comfort that often arise on the device.

These two paths suggest actionable levers by which firms might influence consumers' willingness to self-disclose. For example, if firms wish to encourage consumers to be more self-disclosing in survey responses, our findings suggest that they should design surveys in a way that enhances respondents' feelings of psychological comfort—such as by exposing them throughout the survey to images or even sounds that are comforting or relaxing. From a consumer-welfare perspective, the mechanisms also have implications for consumers who want to avoid being too self-disclosing in certain contexts; for instance, they might consider eschewing their phone for their laptop when writing a work email or when responding to long, open-ended survey questions.

Extensions to Emerging Technologies and Boundary Conditions

One suggested area for future research is exploring whether the observed effects extend to newer technologies. Here, we argued that the small size of smartphone screens has an attention-narrowing effect that heightens consumers' willingness to self-disclose when generating content. Given that some new technologies—such as smart watches—have screens so small that they render typing extremely difficult, we predict that attempting to write on such small devices may prevent consumers from disclosing altogether. Another emerging technology to consider is voice-enabled assistants such as iPhone's Siri or Amazon's Alexa. Would the observed effects on smartphones versus PCs still hold if consumers used voice commands instead of written responses to disclose personal information? One might predict, for example, that sharing personal information verbally—rather than writing it—might evoke the psychological experience of face-to-face interaction, which (as noted previously) has been shown to reduce disclosure relative to written communication through computers (e.g., Joinson 2001). We believe that these are important and intriguing questions that merit future investigation.

Future research could also further explore the role that the psychological comfort associated with one's smartphone plays in enhancing depth of disclosure on the device. For example, incidental experiences that precede disclosure—such as the extent of comfort derived from browsing certain online content on the device—may influence users' subsequent willingness to disclose in the short term, regardless of the device on which they are responding. In this case, firms may want to expose consumers to certain types of comforting or relaxing content prior to eliciting sensitive information from them. Moreover, to the extent that this psychological comfort arises from one's established associations with the device (Melumad and Pham 2020), consumers might be more willing to respond to personal or sensitive questions on their own smartphone than on an otherwise similar phone belonging to someone else. This bears important implications for medical professionals, for example, who have begun to increasingly administer surveys to patients using in-office tablets. Our findings suggest that medical professionals might consider sending sensitive survey questions to their patients so that they can respond instead on their personal smartphone.

Future research could also test for boundaries of the types of information that consumers are willing to reveal on their smartphone versus PC. While we found evidence for the effect among some highly sensitive disclosures (e.g., providing one's bankruptcy history or issues with substance abuse in Study 5), many of the disclosures examined in our studies did not involve highly sensitive information—for example, descriptions of restaurant experiences (Study 1). While we do find that the effect extends to admissions of embarrassing or private purchases (Study 4), it is possible that the observed differences across devices may disappear when it comes to disclosures that could be more personally harmful, such as sharing one's social security number or financial information.

Acknowledgments

The authors thank Rachel Zalta and Andres Salazar from Taboola for their data contribution.

Associate Editor

Markus Giesler

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

References

Altman, Irwin and Dalmas Taylor (1973), *Social Penetration: The Development of Interpersonal Relationships*. Oxford, UK: Holt, Reinhart, and Winston.

Andrade, Eduard B., Velitchka Kaltcheva, and Barton Wietz (2002), "Self Disclosure on the Web: Impact of Privacy Policy, Reward, and Company Reputation," *Proceedings of the Association for Consumer Research*, 29 (1), 350–53.

Antoun, Christopher, Mick P. Couper, and Frederick G. Conrad (2017), "Effects of Mobile Versus PC Web on Survey Response Quality: A Crossover Experiment in a Probability Web Panel," *Public Opinion Quarterly*, 81 (S1), 280–306.

Bak, Jin Yeong, Suin Kim, and Alice Oh (2012), "Self-Disclosure and Relationship Strength in Twitter Conversations," in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics (Vol. 2: Short Papers)*, Haizhou Li, Chin-Yew Lin, Miles Osborne, Gary Geunbae Lee, and Jong C. Park, eds. Jeju Island, South Korea: Association for Computational Linguistics, 60–64.

Bak, Jin Yeong, Chin-Yew Lin, and Alice Oh (2014), "Self-Disclosure Topic Model for Classifying and Analyzing Twitter Conversations," in Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), Alessandro Moschitti, Bo Pang, and Walter Daelemans, eds. Doha: Association for Computational Linguistics, 1986–96.

Balani, Sairam and Munmun De Choudhury (2015), "Detecting and Characterizing Mental Health Related Self-Disclosure in Social Media," in *CHI '15: Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. New York: Association for Computing Machinery, 1373–78.

Barak, Azy and Orit Gluck-Ofri (2007), "Degree and Reciprocity of Self-Disclosure in Online Forums," *Cyberpsychology, Behavior, and Social Networking*, 10 (3), 407–17.

Bowling, Ann (2005), "Mode of Questionnaire Administration Can Have Serious Effects on Data Quality," *Journal of Public Health*, 27 (3), 281–91.

Brockmeyer, Timo, Johannes Zimmermann, Dominika Kulessa, Martin Hautzinger, Hinrich Bents, Hans-Christoph Friederich, et al. (2015), "Me, Myself, and I: Self-Referent Word Use as an Indicator of Self-Focused Attention in Relation to Depression and Anxiety," *Frontiers in Psychology*, 6, 1564.

Buskirk, Trent D. and Charles H. Andrus (2014), "Making Mobile Browser Surveys Smarter: Results from a Randomized Experiment Comparing Online Surveys Completed via Computer or Smartphone," *Field Methods*, 26 (4), 322–42.

Carver, Charles S. and Michael Scheier (1981), *Attention and Self-Regulation: A Control Theory Approach to Human Behavior*. New York: Springer.

Castiello, Umberto and Carlo Umiltà (1990), "Size of the Attentional Focus and Efficiency of Processing," *Acta Psychologica*, 73 (3), 195–209.

Chaikin, Alan L., Valerian Derlega, and Sarah J. Miller (1976), "Effects of Room Environment on Self-Disclosure in a Counseling Analogue," *Journal of Counseling Psychology*, 23 (5), 479–81.

Cheever, Nancy, Larry Rosen, L. Mark Carrier, and Amber Chavez (2014), "Out of Sight Is Not Out of Mind: The Impact of Restricting Wireless Mobile Device Use on Anxiety Levels Among Low, Moderate and High Users," *Computers in Human Behavior*, 37, 290–97.

Chen, I-Ping, Chia-Ning Liao, and Shih-Hao Yeh (2011), "Effect of Display Size on Visual Attention," *Perceptual and Motor Skills*, 112 (3), 959–74.

Chen, Ping-Ling and Chih-Wei Pai (2018), "Pedestrian Smartphone Overuse and Inattentional Blindness: An Observational Study in Taipei, Taiwan," *BMC Public Health*, 18 (1), 1342.

Clayton, Russell, Glenn Leshner, and Anthony Almond (2015), "The Extended iSelf: The Impact of iPhone Separation on Cognition, Emotion, and Physiology," *Journal of Computer-Mediated Communication*, 20 (2), 119–35.

Cozby, Paul C. (1973), "Self-Disclosure: A Literature Review," *Psychological Bulletin*, 79 (2), 73–91.

Davis, Deborah and Timothy C. Brock (1975), "Use of First-Person Pronouns as a Function of Increased Objective Self-Awareness and Performance Feedback," *Journal of Experimental Social Psychology*, 11 (4), 381–88.

Derlega, Valerian J. and Alan L. Chaikin (1977), "Privacy and Self-Disclosure in Social Relationships," *Journal of Social Issues*, 33 (3), 102–15.

Derlega, Valerian J., Sandra Metts, Sandra Petronio, and Stephen Margulis (1993), *Self-Disclosure*. Newbury Park, CA: SAGE Publications.

Dienlin, Tobias (2014), "The Privacy Process Model," in *Media and Privacy*, Simon Garnett, Stefan Halft, Matthias Herz, and J.-M. Mönig, eds. Passau, Germany: Stutz, 105–22.

Faraji-Rad, Ali, M. Samuelsen, M. Bendik, and Luk Warlop (2015), "On the Persuasiveness of Similar Others: The Role of Mentalizing and the Feeling of Certainty," *Journal of Consumer Research*, 42 (3), 458–71.

Forgas, Joseph P. (2011), "Affective Influences on Self-Disclosure: Mood Effects on the Intimacy and Reciprocity of Disclosing Personal Information," *Journal of Personality and Social Psychology*, 100 (3), 449–61.

Gifford, Robert (1988), "Light, Décor, Arousal, Comfort, and Communication," *Journal of Environmental Psychology*, 8 (3), 177–89.

Grewal, Lauren and Andrew T. Stephen (2019), "In Mobile We Trust: The Effects of Mobile Versus Nonmobile Reviews on Consumer Purchase Intentions," *Journal of Marketing Research*, 56 (5), 791–808.

Heberlein, Thomas A. and Robert M. Baumgartner (1978), "Factors Affecting Response Rates to Mailed Questionnaires: A Quantitative Analysis of the Published Literature," *American Sociological Review*, 43 (4), 447–62.

Houghton, David J. and Adam N. Joinson (2012), "Linguistic Markers of Secrets and Sensitive Self-Disclosure in Twitter," in *45th Hawaii International Conference on System Science (HICSS)*. Piscataway, NJ: Institute of Electrical and Electronics Engineers, 3480–89.

Hyman, Ira E., S. Matthew Boss, Breanne M. Wise, Kira E. McKenzie, and Jenna M. Caggiano (2010), "Did You See the Unicycling Clown? Inattentional Blindness While Walking and Talking on a Cell Phone," *Applied Cognitive Psychology*, 24 (5), 597–607.

Jiang, Lan, Joandrea Hoegg, Darren W. Dahl, and Amitava Chattopadhyay (2010), "The Persuasive Role of Incidental Similarity on Attitudes and Purchase Intentions in a Sales Context," *Journal of Consumer Research*, 36 (5), 778–91.

John, Leslie K., Alessandro Acquisti, and George Loewenstein (2011), "Strangers on a Plane: Context-Dependent Willingness to Share Sensitive Information," *Journal of Consumer Research*, 37 (5), 858–73.

Joinson, Adam N. (2001), "Self-Disclosure in Computer-Mediated Communication: The Role of Self-Awareness and Visual Anonymity," *European Journal of Social Psychology*, 31 (2), 177–92.

Jourard, Sydney M. and P. Lasakow (1958), "Some Factors in Self-Disclosure," *Journal of Abnormal and Social Psychology*, 56 (1), 91–98.

Kiesler, Sara, Jane Siegel, and Timothy W. McGuire (1984), "Social Psychological Aspects of Computer-Mediated Communication," *American Psychologist*, 39 (10), 1123–34.

Kim, Jinsuk and Kathryn Dindia (2011), "Online Self-Disclosure: A Review of Research," in *Computer-Mediated Communication in Personal Relationships*, K. B. While and L. M. Web, eds. New York: Peter Lang, 156–80.

King, Ed (2016), "Election Day Tweets Scraped from Twitter on November 8, 2016," Kaggle, https://www.kaggle.com/kinguistics/election-day-tweets.

Lin, Ming-I Brandon and Yu-Pin Huang (2017), "The Impact of Walking While Using a Smartphone on Pedestrians' Awareness of Roadside Events," *Accident Analysis and Prevention*, 101, 87–96.

Manchanda, Puneet, Jean-Pierre Dubé, Khum Yong Goh, and Pradeep K. Chintagunta (2006), "The Effect of Banner Advertising on Internet Purchasing," *Journal of Marketing Research*, 43 (1), 98–108.

Mavletova, Aigul and Mick P. Couper (2013), "Sensitive Topics in PC Web and Mobile Web Surveys: Is There a Difference?" *Survey Research Methods*, 7 (3), 191–205.

Melumad, Shiri, J.Jeffrey Inman, and Michel Tuan Pham (2019), "Selectively Emotional: How Smartphone Use Changes User-Generated Content," *Journal of Marketing Research*, 56 (2), 259–75.

Melumad, Shiri and Michel Tuan Pham (2020), "The Smartphone as a Pacifying Technology," *Journal of Consumer Research*, forthcoming.

Miwa, Yoshiko and Kazunori Hanyu (2006), "The Effects of Interior Design on Communication and Impressions of a Counselor in a Counseling Room," *Environment and Behavior*, 38 (4), 484–502.

Moon, Youngme (2000), "Intimate Exchanges: Using Computers to Elicit Self-Disclosure from Consumers," *Journal of Consumer Research*, 26 (4), 323–39.

Murphy, Gillian, John A. Groeger, and Ciara M. Greene (2016), "Twenty Years of Load Theory—Where Are We Now, and Where Should We Go Next?" *Psychonomic Bulletin and Review*, 23 (5), 1316–40.

Okdie, Bradley (2011), Blogging and Self-Disclosure: The Role of Anonymity, Self-Awareness, and Perceived Audience, doctoral dissertation, Department of Psychology, University of Alabama.

Omarzu, Julia (2000), "A Disclosure Decision Model: Determining How and When Individuals Will Self-Disclose," *Personality and Social Psychology Review*, 4 (2), 174–85.

Panova, Tayana and Xavier Carbonell (2018), "Is Smartphone Addiction Really an Addiction?" *Journal of Behavioral Addictions*, 7 (2), 252–59.

Pennebaker, James W. and Anna Graybeal (2001), "Patterns of Natural Language Use: Disclosure, Personality, and Social Integration," *Current Directions in Psychological Science*, 10 (3), 90–93.

Pennebaker, James W., Ryan L. Boyd, and Kayla Jordan (2015), *The Development and Psychometric Properties of LIWC 2015*. Austin: University of Texas at Austin.

Ransbotham, Sam, Nicholas H. Lurie, and Hongju Liu (2019), "Creation and Consumption of Mobile Word of Mouth: How Are Mobile Reviews Different?" *Marketing Science*, 38 (5), 773–92.

Ravichander, Abhilasha and Alan Black (2018), "An Empirical Study of Self-Disclosure in Spoken Dialogue Systems," *Proceedings of the SIGDIAL 2018 Conference*, 253–63.

Rituparna (2018), "FIFA World Cup 2018 Tweets: A Collection of Tweets During the 2018 FIFA World Cup," Kaggle (accessed March 6, 2020), https://www.kaggle.com/rgupta09/world-cup-2018-tweets.

Ruppel, Erin K., Claire Gross, Arrington Stoll, Brittnie S. Peck, Mike Allen, and Sang-Yeong Kim (2017), "Reflecting on Connecting: Meta-Analysis of Differences Between Computer-Mediated and Face-to-Face Self-Disclosure," *Journal of Computer-Mediated Communication*, 22 (1), 18–34.

Sassenberg, Kai, Margarete Boos, and Sven Rabung (2005), "Attitude Change in Face-to-Face and Computer-Mediated Communication: Private Self-Awareness as Mediator and Moderator," *European Journal of Social Psychology*, 35 (3), 361–74.

Short, John, Ederyn Williams, and Bruce Christie (1976), *The Social Psychology of Telecommunications*. London: John Wiley & Sons.

Skierkowski, Dorothy and Rebecca M. Wood (2012), "To Text or Not to Text? The Importance of Text Messaging Among College-Aged Youth," *Computers in Human Behavior*, 28 (2), 744–56.

Spears, Russell and Martin Lea (1994), "Panacea or Panopticon? The Hidden Power of Computer-Mediated Communication," *Communication Research*, 21 (4), 427–59.

Toninelli, Daniele and Melanie Revilla (2016), "Smartphones vs. PCs: Does the Device Affect the Web Survey Experience and the Measurement Error for Sensitive Topics? A Replication of the Mavletova & Couper's 2013 Experiment," *Survey Research Methods*, 10 (2), 153–69.

Vahedi, Zahra and Alyssa Saiphoo (2018), "The Association Between Smartphone Use, Stress, and Anxiety: A Meta-Analytic Review," *Stress and Health*, 34 (1), 347–58.

Veltri, Guiseppe A. and Andriy Ivchenko (2017), "The Impact of Different Forms of Cognitive Scarcity on Online Privacy Disclosure," *Computers in Human Behavior*, 73, 238–46.

Wallace, Patricia (1999), *The Psychology of the Internet*. Cambridge, UK: Cambridge University Press.

Walther, Joseph B. (1996), "Computer-Mediated Communication: Impersonal, Interpersonal, and Hyperpersonal Interaction," *Communication Research*, 23 (1), 3–43.

Wang, Yi-Chia, Moira Burke, and Robert Kraut (2016), "Modeling Self-Disclosure in Social Networking Sites," *Proceedings of the 19th ACM Conference*, 74–85.

Wedel, Michel and P.K. Kannan (2016), "Marketing Analytics for Data-Rich Environments," *Journal of Marketing*, 80 (6), 97–121.

Weisband, Suzanne P. and Sara Kiesler (1996), "Self-Disclosure on Computer Forms: Meta-Analysis and Implications," in *Proceedings of the Conference on Human Factors in Computing Systems*. New York: Association for Computing Machinery, 3–10.

Wells, Tom, Justin T. Bailey, and Michael W. Link (2014), "Comparison of Smartphone and Online Computer Survey Administration," *Social Science Computer Review*, 32 (2), 238–55.